Chaotic Search of Emergent Locomotion Patterns for a Bodily Coupled Robotic System

Yoonsik Shim[1] and Phil Husbands[1]

[1]Centre for Computational Neuroscience and Robotics, University of Sussex, Falmer, Brighton, UK
Y.S.Shim@sussex.ac.uk

Abstract

We study a novel deterministic online process for the exploration and capture of possible locomotion patterns of a simulated articulated robot with an arbitrary morphology in an unknown physical environment. The robot controller is modelled as a network of neural oscillators which are coupled indirectly through physical embodiment. Goal directed exploration of coordinated motor patterns is achieved by a chaotic search method using adaptive bifurcation. The phase space of the indirectly coupled neural-body-environment system contains multiple phase-locked states each of which is a candidate for driving efficient locomotion. By varying the chaoticity of the system as a function of evaluation signal, it is able to chaotically wander through various phase-locked states and stabilise on one of the states matching the given criteria. The nature of the weak coupling through physical embodiment ensures that only physically stable locomotion patterns emerge as coherent states, which implies the emergent pattern is well suited for open-loop control with little or no sensory inputs.

Introduction

Properly coordinated rhythmic motor behaviours are ubiquitous in animals. From insects to humans, locomotive ability is one of the most fundamental survival mechanisms to have evolved. As has been increasingly pointed out over the past few years (Pfeifer and Iida, 2004), studying neural circuitry underlying the generation of rhythmic motor behaviour in isolation ignores the considerable advantage that can be obtained from incorporating the the physical body and its environment - an approach that can significantly reduce the amount of information needed to develop successful motor patterns.

This naturally led to efforts to exploit ready-made functionality provided by the given physical properties of an embodied system for the automatic generation of motor movement. One such line of enquiry involves using frequency adaptive oscillators that can be entrained to the resonant frequency of the mechanical system (Buchli et al., 2006), including the use of chaotic frequency scaling (Raftery et al., 2008). Although frequency adaptation to a given physical body accounts for a major part of the properties of locomotion, we believe that, in general, the appropriate phase relationship between each limb should take priority among other aspects when dealing with the creation of new motor patterns. One of the seminal works from this perspective is the exploration and acquisition of motor primitives, for a simple robot, using a mechanism which is embodied as a coupled chaotic field (Kuniyoshi and Suzuki, 2004). Those researchers modelled an extreme version of embodied coupling that had no electrical connection between neural units at all: they were only coupled indirectly through body-environment interactions. The neural oscillators were implemented using a simple logistic map with chaotic behaviour, and the system dynamics rapidly developed to a stable, coherent rhythmic motion by using mutual entrainment between the neural circuit and the body-environment interactions. The process was completely deterministic. Later work (Kuniyoshi and Sangawa, 2006) dealt with a more biologically plausible system in which a realistic musculo-skeletal model was employed and the neural control circuit consisted of a model CPG. While these previous studies have developed detailed biological models that have significant implications for the understanding of motor development, concrete general methodologies for applying such techniques to the automatic generation of desired motor patterns for autonomous robots remains a challenge.

In this paper we build on the prior work outlined above, extending and generalising it as we attempt to develop a generally applicable methodology for neural-body-environment coupled systems, based around self-organisation through chaotic dynamics. We present a study of goal directed online exploration of rhythmic motor patterns in a oscillator system coupled through physical embodiment, specifically generating forward locomotion behaviours without prior knowledge of the body morphology or its physical environment. This is explored in the context of a simulated limbed robot. In an important departure from the previous work outlined above, in order to explore and drive system dynamics toward a desired state, we employ the concept of Chaotic Mode Transition with external feedback (Davis, 1990), which exploits the intrinsic chaoticity of a system orbit as a perturbation force to explore multiple synchronised states of the system,

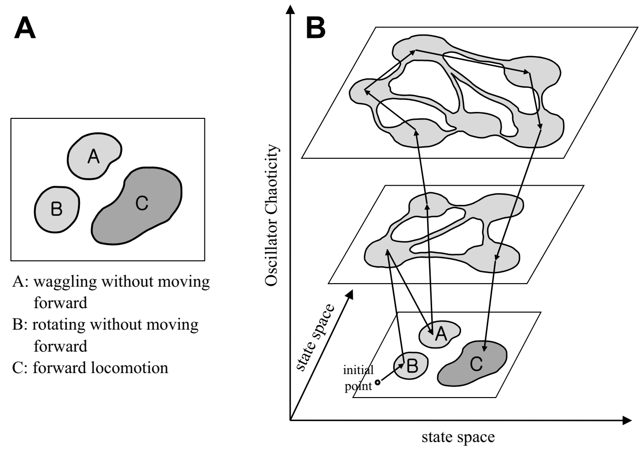


Figure 1: (A) A conceptual illustration of the state space of a neuro-body-environment system coupled through physical embodiment, which consists of three basins of attraction (A,B,C) with different performances. (B) An exploration process to find the desired attractor, C, by varying the complexity of the state space landscape. Lump spaces and narrow passages in the landscapes of higher complexities represent quasi-attractors and itinerant pathways respectively.

and stabilises the orbit by decreasing its chaoticity according to a feedback signal that evaluates the behaviour. This enables the system to perform a deterministic search guided by a global feedback signal from the physical system, which facilitates an active exploration toward a desired behaviour. This research is intended to open up new directions in the exploitation of chaos as a self-organising principle in embodied autonomous systems, as well as to potentially shed light on its role in biological systems.

Chaoticity as Perturbation Strength

Conventional optimisation strategies generally use stochastic perturbations on system parameters for search space exploration. However, a few studies address the effectiveness of chaotic dynamics as behaving like a stochastic source (Ott et al., 1994), and have found that a deterministic chaotic generator outperforms a stochastic random explorer (Morihiro et al., 2008). In these cases, the chaotic dynamics acts as an external module generating perturbations that cause system parameters to wander in parameter space. However, as we shall see, adaptive chaotic search methods using bifurcation to chaos can directly drive the phase orbit of a bodily coupled system for exploration because of the endogenous existence of chaotic dynamics in the system itself.

The general idea of applying a chaotic search method which uses adaptive parametric feedback control had been previously presented in the field of optical sciences (Aida and Davis, 1994) and for memory search (Nara and Davis, 1992). It has been argued that this method should be generally applicable when the target device is capable of supporting a variety of stable modes, with chaotic transitions existing between them, which interact with their environment and give a feedback signal evaluating whether the mode is suitable or not. Chaotic transitions allow the system to try each of the modes sequentially, and the mode which is evaluated as suitable is selected and stabilised by changing a device parameter to take it into a multistable regime. An indirectly coupled neuro-body-environmental system, such as the one used in this paper, has the required characteristics of such a device, including multiple coordinated oscillation modes. It is known that a properly designed coupled oscillator system can have multiple synchronised states which exhibit stable oscillations (Feudel and Grebogi, 1997), and the structure of emergent behaviour in these systems often reflect the spatial distribution of coupling strengths (Kaneko, 1994). Accordingly, a network of oscillators coupled through physical embodiment forms multiple synchronised states which reflects the body schema and its interaction with the environment.

A conceptual description of the chaotic search process is briefly illustrated in Fig. 1. The goal of the system can be regarded as finding and becoming entrained in the basin of a particular attractor which has high performance (denoted by C) while escaping from the low performing attractors (A and B) regardless of the initial point in the state space. The idea is to ‘open’ a new pathway which connects those isolated basins through use of an additional dimension afforded by changing the system dynamics through tuning the chaoticity according to the evaluation signal. The orbit will visit and evaluate each of the attractor (A,B,C) systematically yet chaotically by adaptively varying the bifurcation parameter of the system according to the feedback signal until it reaches the basin of the desired attractor. The process can be interpreted as a deterministic version of trial-and-error search which exploits the chaotic behaviour of system. For the first time, this study attempts to implement and integrate these concepts into an autonomous neuro-body-environment system, making use of a continuous-time dynamical system framework.

Method

The architecture of the neural part of the generic system developed is based on (Kuniyoshi and Sangawa, 2006), but with a more compact and modular configuration for each joint of the limbed robot. It is intended to be applicable to a wide range of robotic systems. The architecture consists of a number of identical control modules connected to each of the body parts in their environment. Each neuro-motor-joint system which receives afferent sensory input and gives motor output can be encapsulated as a single *motor unit*, and the whole system consists of identical motor units whose number is the same as the number of degrees of freedom of the robot (Fig. 2). The signal from the sensor of a motor unit (in most case a mechanosensory information) is fed, with opposite signs, to both of the pair of electrically unconnected oscillators that each motor unit contains. This configura-

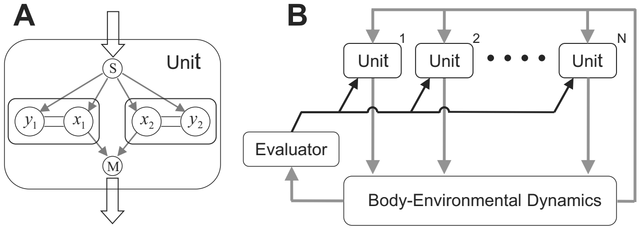


Figure 2: (A) A *motor unit* for a single degree of freedom in the joint-motor system. A unit consists of two electrically disconnected oscillators, which receive indirect integrated information of other oscillators in the system from the sensor (S), via environmental coupling, and give a control signal to the motor (M). (B) A neural-body-environment system whose body has N degrees of freedom. The complexities of all units are altered according to a global evaluation signal.

tion eliminates muscle redundancies by constraining joint-motors to be operated only by an antagonistic actuator pair, thus giving more weight to inter-limb interactions.

The control signals for the basic motor patterns are generated by central pattern generators (CPG), which are composed of a collection of neurons that produces an oscillatory signal for various locomotor patterns by synchronisation with the movement of the physical systems. The model consists of coupled Bonhoeffer-van der Pol (BVP, or Fitzhugh-Nagumo) oscillators which are widely studied as models of pacemaking cells and interlimb coordination. A particularly interesting feature of coupled BVP equations, that allows adjustment of the complexity of the system orbit, had been presented by (Asai et al., 2003). A pair of coupled BVP oscillators generates a stable limit cycle when the two control inputs are the same, but a quasiperiodic/chaotic orbit otherwise. Another interesting feature of the BVP model is flexible phase locking (Ohgane et al., 2009), where the phase relationship between CPG activity and body motion can be flexibly locked according to a loop delay. This is a beneficial feature for covering a range of sensorimotor delays originated from different body-environment configurations. A pair of oscillators for a motor unit i, dealing with its sensory input, is described by the following equations:

$$\tau \frac{dx_{1,i}}{dt} = c(x_{1,i} - \frac{x_{1,i}^3}{3} - y_{1,i} + z_1) + \delta(I_1(s_i) - x_{1,i}) \quad (1)$$

$$\tau \frac{dy_{1,i}}{dt} = \frac{1}{c}(x_{1,i} - by_{1,i} + a) + \varepsilon I_1(s_i) \quad (2)$$

$$\tau \frac{dx_{2,i}}{dt} = c(x_{2,i} - \frac{x_{2,i}^3}{3} - y_{2,i} + z_2) + \delta(I_2(s_i) - x_{2,i}) \quad (3)$$

$$\tau \frac{dy_{2,i}}{dt} = \frac{1}{c}(x_{2,i} - by_{2,i} + a) + \varepsilon I_2(s_i) \quad (4)$$

where τ is a time constant, and a=0.7, b=0.675, c=1.75 are the fixed parameters of the oscillator. δ=0.013 and ε=0.022 are coupling strength for afferent input $I(s)$ which is a function of the actual sensor value s. The time constant, which represents the frequency of the oscillator, was set to τ=0.8 throughout this work, as this was found to be an appropriate value. z_1 and z_2 are control parameters for adjusting the chaoticity of the motor unit. Their difference (z_2-z_1) changes identically in all motor units as a function of the evaluation signal, which will act as the bifurcation parameter for the chaotic search with adaptive feedback. In the stable regime where z_1 and z_2 are symmetric, (Asai et al., 2003) found that the two coupled BVP equations exhibit bistable phase locking of their oscillations in a parameter range of $0.6 < z_1 = z_2 < 0.88$. From the observation of a number of experiments on the oscillator dynamics, to ensure a higher probability of multistability of the system, we chose to fix $z_2 = 0.73$ and to vary z_1.

Evaluation and Feedback

The coherent integration of a performance evaluation signal that is able to control the chaoticity of the system is an important contribution of the current work. In the experiments to be described next, the performance evaluation signal E is measured by the forward speed of the robot. Since the system has no prior knowledge of the body morphology of the robot, it does not have direct access to the direction of movement nor of information on body orientation. In order to facilitate steady movement in one direction without gyrating in a small radius, a temporal integration of the velocity of the center of mass was formulated as an evaluation function. The center of mass velocity of a robot is continuously averaged over a certain time window and its magnitude was used as the performance of system. The performance signal E at any time instance can be calculated by applying a leaky integrator equation to the velocity vector as

$$E(t) = |\bar{\mathbf{v}}|, \quad \tau_E \frac{d\bar{\mathbf{v}}}{dt} = -\bar{\mathbf{v}} + \mathbf{v} \quad (5)$$

τ_E is the time scale of integration which is larger than that of an oscillator (slower than the oscillator period), but typically not exceeding it by more than an order of magnitude.

A global feedback signal determines the degree of chaoticity of an oscillator network. The bifurcation parameter for feedback control is continuously modified by an amount governed by the evaluation signal. If the current entrained state is not satisfactory, parameter μ is increased to where the orbit will follow quasiperiodic or chaotic dynamics, and when a satisfactory pattern appears, μ is decreased so that the satisfactory mode becomes stable. The adaptive control parameter μ ($= z_2 - z_1$) is described as follows:

$$\tau_\mu \frac{d\mu}{dt} = -\mu + G(E) \quad (6)$$

$$G(E) = \frac{\mu_c}{1 + e^{P(E)}}, \quad P(E) = \frac{16E}{E_d} - 8 \quad (7)$$

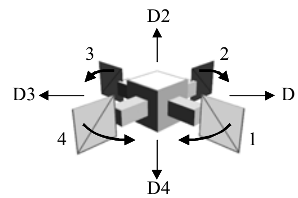
As described in the last section, z_2 (Equation 3) if fixed, hence z_1 (Equation 1) varies as μ changes. $G(E)$ is a monotonically decreasing sigmoidal function of locomotion performance E (Fig. 3). τ_μ determines the time scale of the change of μ and is normally set faster ($\tau_\mu < T$) than the oscillation period (T) of the controller. If its value is too high, stabilisation of the system dynamics is significantly delayed which results in a partition mismatch (Aida and Davis, 1994). If it is too low, μ tends to fluctuate according to the undulation of the robot movement which acts as a disturbance for stabilisation, or the system can become locked in a ring of undesirable patterns in a regime of intermediate chaoticity. We used $\tau_\mu = 0.5T$ throughout this work. The evaluation function $G(E)$ determines the level of chaoticity by varying μ in the range [0,μ_c] where μ_c is the maximum level of chaoticity of the system. From the analysis of a single BVP oscillator it is well known that it shows Hopf bifurcation with the increase of the parameter z (Nomura et al., 1993). An analytically estimated critical value of z for equations (1) and (2), without its coupling term, is $z{\approx}0.38247$, which indicates that the maximum possible value of μ_c is $0.73 - 0.38247 = 0.34753$. However, because the situation is different from the dynamics of a single oscillator, experiments on the robotic system presented here revealed that the actual behavioural criticality of z varies slightly among different body and environmental settings. Hence we chose $\mu_c = 0.35$, taking into consideration the asymptotic characteristic of the sigmoidal function G. E_d indicates the desired locomotion performance of a given robot. However we do not have prior knowledge of how much performance it can achieve. Hence the dynamics of E_d is modelled using the idea of a goal setting strategy (Barlas and Yasarcan, 2006). With this concept the expectation of a desired goal is influenced by the history of the actual performance experienced in the past. When the robot has already achieved high performance during a certain period in the past, the performance expectation increases. The performance expectation decays if it is not being met by the actual performance. We integrate this strategy in terms of simple continuous dynamics for E_d, which slowly decays toward the current performance. This can be simply described by a leaky-integrator equation:

$$\tau_d \frac{dE_d}{dt} = -E_d + E \tag{8}$$

where τ_d is set larger than τ_E. E_d functions as a temporal average of E for a certain time window. Since E_d continuously decays toward E, the changing speed of control parameter μ depends both on E and τ_d. Therefore τ_d determines the depth and the duration of chaotic wandering.

Experiments and Results

Initial experiments with the framework described above used the simple simulated robot shown in Fig. 3: a four-armed aquatic swimmer with fins at the end of each arm placed in a simulated hydrodynamic planar environment. The robot was modelled using ODE (Smith, 1998). A joint-motor of the robot was modelled using a pair of servo motors which generate torques in opposite direction. These motors are used as effectors for the neuronal output by varying their desired angular speed according to the simulated muscle force used by (Ekeberg, 1993). The functional structure of bodily coupling between motor units is formed by the transmission of hydraulic reaction forces of one limb to the others through body articulation. Each fin was modelled as a nonlinear torsional spring and its bending angle (θ) was fed to the corresponding motor unit. The fin angle implements the stretch receptor at each side of fin, so the afferent input I in the equations (1) and (3) were defined as: $I_1(\theta) = H(k\theta)$ and $I_2(\theta) = H(-k\theta)$ where k ($= 2.5$) is input gain and $H(x)$ is heaviside function. Joint axes and motor unit arrangements were set to be bilaterally symmetric which is a dominant feature throughout the animal world. The radial symmetry of the body morphology ensures that possible locomotion behaviours are not restricted to longitudinal directions. The radially symmetric shape in a 2D underwater environment is interesting because it makes generating continuous asymmetric propulsion forces challenging; in other words forward locomotion is non-trivial. The agent will not be able to move in a single direction unless the movements of all four arms are successfully synchronised with appropriate phase differences. The other parameters used for the search process was $\mu_c = 0.35$, $\tau_E = 5T$ and $\tau_d = 5\tau_E$



4-Fin Swimmer	
torso dimension (m)	0.2× 0.2× 0.2
arm dimension (m)	0.075× 0.075× 0.15
torso weight (Kg)	1.6
arm weight (Kg)	0.34 (× 4)
joint range (rad)	± 1.0
fin dimension (m)	0.2× 0.2
fin weight (Kg)	0.005
fin stiffness (N/m)	0.1
fin damping (Ns/m)	0.045
fluid density (Kg/m^3)	1000.0

Figure 3: The 4-Fin Swimmer and its parameters. The arrows at each joint describe the direction of rotation. Arrows D1-D4 represent the possible directions of movement.

Observation of Emergent Behaviours

First, we fixed the control parameter to a target value ($\mu = 0$, no chaotic search) and ran the simulation to see what kinds of behaviours emerged from various initial states. Numerous test was done in order to observe and categorise the behaviours that emerged from the system. Basic movement behaviours were categorised into motion in four directions (along the body axes D1,D2,D3 and D4 as shown in Fig. 4) which met expectations given the symmetric shape of the swimmer. For each direction of movement, four different behaviours were observed and classified according to the locomotion performance. These are straight movement, moving in medium radius circles, moving in small radius circles, and moving in/out in a spiral. Each circling locomotion can be either clockwise or counterclockwise. Also there were non-locomotion movements such as rotation or vibrating at a fixed position, and completely symmetric leg movements

Pattern	# of variations	Avrg E
1. straight (ST)	4 body orientations	0.45
2. medium R (MR)	8 (4×(CW/CCW))	0.25
3. small R (SR)	8 (4×(CW/CCW))	0.2
4. spiral (SP)	8 (4×(CW/CCW))	0.02-0.3
5. rotate (RO)	2 (CW/CCW)	0.03
6. vibration (VB)	2 (D1-D3 / D2-D4)	0.03
7. bound antiphase (BA)	1	0.0

Table 1: Categories of emergent behaviours. The variations of straight swimming are in 4 different body orientations. Circular movements (pattern 2,3,4) have 8 variations by including two circling directions. Vibration has 2 variations which are in direction of D1-D3 and D2-D4.

resulting in no movement (bound antiphase). The categories of emergent behaviours of the swimmer robot and their average performances are shown in Table 1, which indicates that the total number of movement patterns is 33.

In order to quantify an emergent pattern and its temporal dynamics we developed a method we call a *Feature Index* (FI) plot which is inspired by multivariable data binning techniques. A feature index is a scalar value which is calculated from the powered sum of the bin indices of the phase differences between each DoF. Therefore, a feature index can uniquely represent a given motor coordination. Since the phase difference alone cannot capture the difference of motor amplitudes we used two feature indices: one for the phase relationship and one for the amplitude relationship. If we define N phase differences of the limb movements, the feature index F can be written as:

$$F = \sum_{i=1}^{N} k_i B^{i-1}, \quad k_i \in \mathbb{Z} \tag{9}$$

$$k_i = (d_i - d_{min}) \text{ div } \{(d_{max} - d_{min})/B\} \tag{10}$$

where w is the width of a bin, B is the number of bins, and d_i is the ith wrapped phase difference which has the range [d_{min},d_{max}]. The feature index for the amplitude relationship uses the phase differences between two antagonistic motor commands for d_i. The range of wrapped phase difference were [$-\pi$,π] for the phase index and [0,2π] for the amplitude index which indicates the phase difference of π between antagonistic motor signal is producing maximum amplitude. The FI plots of four different straight locomotions and the other behaviours are depicted in Fig. 4 using the following four phase differences: leg 1-4, leg 2-3, leg 1-2 and leg 4-3.

Dynamics of Chaotic Search

The stable dynamics of the system begins to fluctuate as μ increases, exhibiting a series of transient dynamics from quasiperiodicity to chaos. Fig. 5 shows the chaoticity of the system with different control parameters. In the higher chaotic regime complex transitory dynamics similar

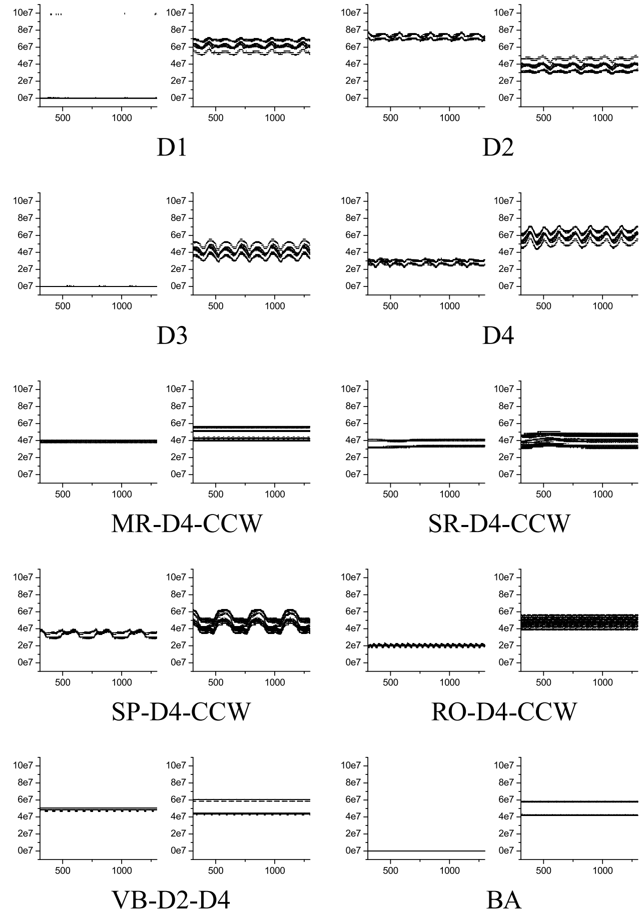


Figure 4: Limb cycle number vs. feature indices. In each pair of plots, a phase plot is on the left and an amplitude plot is on the right. From D1 to D4 are plots of straight locomotion in each direction. The next four plots are from the circular movements whose body orientation are D4 and rotating direction are counterclockwise. The last two plots are for vibration and bound antiphase.

to chaotic intermittency occurs which drives the system to briskly explore the phase space. To see the effect of chaotic search, the distributions of visits to each of the behaviour identified in Table 1 was investigated under the presence and absence of chaotic search. 100 simulations were performed for each case and the visiting counts of seven major behaviours were recorded. Fig. 6 shows a clear difference between the visiting ratios of the two cases, suggesting the effectiveness of chaotic search (B and C) which tended to settle on effective straight motion. In the search with fixed desired performance (Fig. 6B) any pattern below the criteria did not appear while the case of flexible E_d (Fig. 6C) shows a wider range of behaviours although the highest performing patterns still dominate. During the search process all variables and control parameters vary continuously as parts of the neuro-body-environment system, and the time evolution plots (Fig. 7) show that the stabilisation and destabilisation of the system occurs repeatedly in a trial-and-error manner

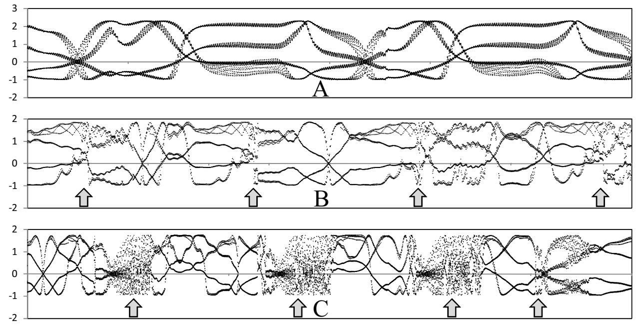


Figure 5: Poincare plots of the output of oscillators which correspond to the flexor neurons for legs 0 and 1 with different value of μ ((A) 0.2, (B) 0.34, (C) 0.346). We can see weak and strong chaotic intermittencies (the regions indicated by arrows) in high μ (B,C) while there is smooth and periodic transition of phase relationships in A.

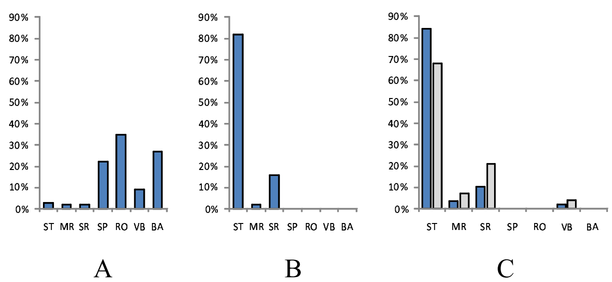


Figure 6: Visiting ratio distribution. (A) No chaotic search. (B) Search with $E_d = 0.2$. (C) Search with adaptive E_d as in Equation 11. Lighter shaded bars indicate visiting ratios in exclusion of ST-D4 pattern through the deep-path (see text).

until it settles on an effective form of locomotion.

Bad-Lock and Deep-Path

Although the system exploits chaotic dynamics for the exploration of motor patterns, unwanted synchronisation between chaotic movements of limbs, resulting in low performance (*bad-lock*), can arise from some initial conditions. In the case of fixed E_d, a local minimum was occasionally observed in which the system dynamics are locked in a narrow range of phase differences while the precise values of variables vary chaotically (Fig. 8). Although this is undesirable for the purpose of this work, it should be noted that this phenomena is observed in real biological systems (e.g. in walking and heartbeat rhythms). The bad-lock phenomena occurred more frequently if we set μ_c below the onset of chaos, indicating that the system has less exploratory 'perturbation force' when using low chaoticity.

Adaptive E_d was successful in enabling the goal seeking strategy for the unknown robotic system, as well as suppressing the bad-lock local minima outlined above by introducing an additional slow variable to the system. However another kind of deficiency, so called *deep-path*, was sometimes observed in this case. This involves the orbit becoming entrained in some periodic state for a long time before it eventually reaches the desired state (Fig. 9). This is due to the time spent in the chaotic regime becomes very short because the difference between E and E_d is too small, resulting in the system taking a long time to escape from the local minimum. The possibilities of bad-lock and deep-path always exist because the system is fully deterministic without stochastic sources, but it should be possible to reduce them by using more sophisticated goal seeking strategies.

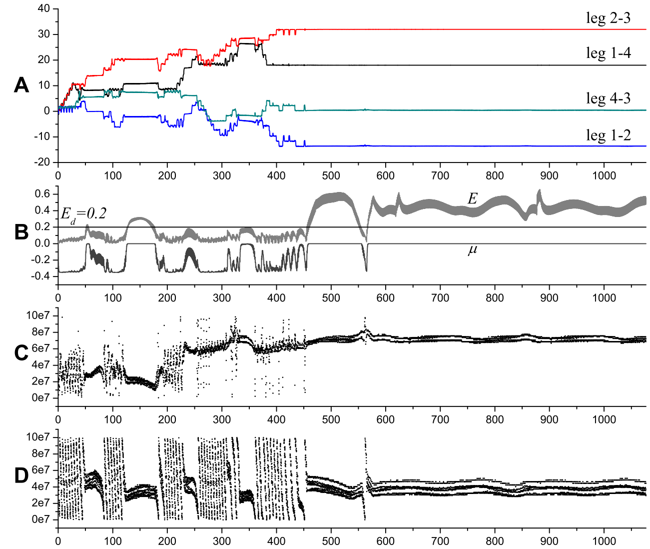


Figure 7: Time evolution of the search process. (A) Unwrapped phase differences between legs. (B) Performance and control parameters. (C,D) Phase and amplitude feature indices.

Physical Stability for Open Loop Control

Previous work on embodied coupling (Pitti et al., 2009) showed that the causal information flow between the controller and physical system is highly biased toward the sensor-to-motor direction, suggesting the controller strongly exploits the body-environment dynamics. Since the neuro-body-environment system used in the current paper is weakly coupled only through physical embodiment it can be inferred that the emergence of movement patterns is highly influenced by the dynamic stability of locomotion. Therefore we hypothesise that the more dynamically stable movement patterns remain longer as coherent states. A previous study (Iida and Pfeifer, 2004) provide the evidence that the intrinsic body dynamics of a properly designed controller-body system can self-stabilise into a periodic locomotion pattern without any sensory input. From the experiment in our study, we have shown that chaotic search of locomotion using a bodily coupled system is capable of naturally finding such stable patterns. This feature, together with the ready-built servo controller means the robot should be able to perform stable locomotion in an open-loop manner without any sensory information. This accomplishes "cheap" locomo-

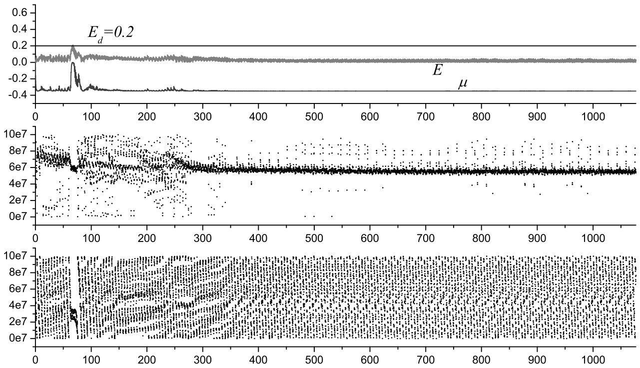


Figure 8: Local minima with fixed $E_d = 0.2$. The phase feature index plot (middle) indicates that the behaviour is locked around the vibrating (VB) pattern while the amplitudes fluctuate periodically.

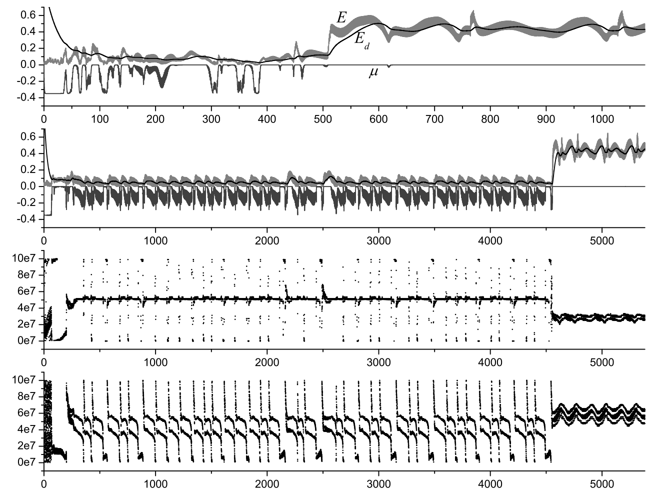


Figure 9: Deep path in the search process with adaptive E_d. The uppermost graph is an example of the typical search process, and the lower three graphs show the deep-path. The system is locked in a periodic state for a long time (see the time length) with very short duration of chaotic perturbation then eventually stabilises on the straight locomotion.

tion, meaning that we should be able to readily capture a wide range of useful transient patterns which appear during the search process without being stabilised.

We tested this using a 'damaged' version of the robot by removing one of its fins, where there is no stable pattern when $\mu = 0$ but there exist a series of useful transient patterns. The chaotic search process was run for the 3-fin swimmer, and if some high performing pattern appeared the sensory input was gradually decayed to zero. We call this process *pattern capturing* for open-loop control rather than *acquiring* because it does not deal with the cortical memorisation of discovered patterns. The time course of the search process of the damaged robot (Fig. 10a) shows multiple transient patterns appear for a while, with high performing patterns among them. After the sensory inputs are removed the captured pattern is stably retained, providing fast locomotion; successful open-loop control is achieved. In order to see the dynamic stability of the captured behaviour, an external perturbation was applied by exerting random forces to each of fins (Fig. 10c). The stability of locomotion was remarkable, as the robot maintained a good locomotion performance even when the perturbation strength was over 200% of the average hydraulic force the fin receives during normal locomotion.

Discussion

We have modelled and investigated the emergent behaviours of a neuro-body-environment system coupled indirectly through physical embodiment and have shown the efficacy of exploring useful motor patterns by applying a novel chaotic search method. The whole system is treated as a single high dimensional continuous dynamical system containing intrinsic chaos as a necessary driving force for the exploration of its own dynamics. The search process was completely deterministic, and was able to selectively entrain the system orbit to one of the patterns by imposing goal directedness toward a desired behaviour. The emergent locomotion behaviours involved inherently stable physical dynamics, enabling stable open-loop control without a need for sensory information.

The method has been tested with a simple underwater robot, but it is generally applicable to a wide range of different robot morphologies and physical environments. However, further analysis is necessary in order to determine the optimum values of various parameters used in the search process. For example, the time scales of slow dynamics such as evaluation, goal seeking and feedback bifurcation (τ_E,τ_d,τ_μ) influence the search performance as well as the probability of being trapped in a local minima. Preliminary results of investigating the effect of different time scales revealed that the ratio between the time scales for evaluation and goal seeking determines the balance between the 'memorising' and 'forgetting' of patterns during the search process, implying there might be an optimal ratio which allows the system to stay in the chaotic regime for an optimal duration enabling fast search with less local minima. Another crucial factor which influences the system is the amount of bandwidth resulting from the design of body-environment interactions. In the case of the 4-fin swimmer presented here, the functional coupling strength between motor units varies with the body mass. Increased body mass will result in an increased moment of inertia which causes less transmission of the hydraulic force on one leg to the others, and vice versa. Similar effect will be caused by decreasing the density of the surrounding fluid or by increasing fin stiffness.

Our method is also applicable to terrestrial robots where a torque sensor is used for the sensory information. A few examples of initial results of our method applied to other

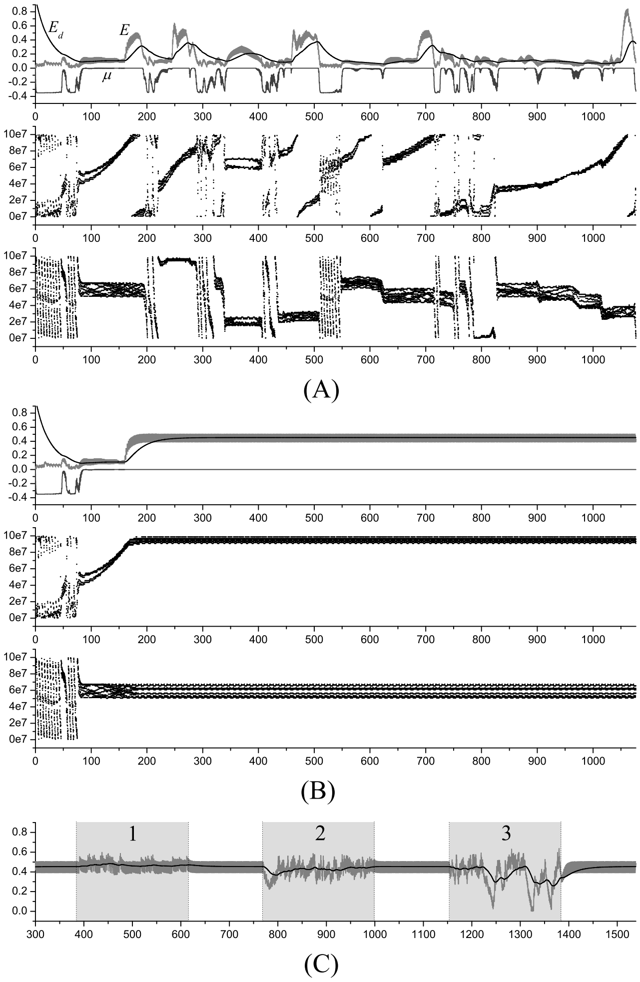


Figure 10: Capturing a transient locomotion pattern. (A) Normal behaviours of damaged robot. (B) Captured pattern by cutting sensory inputs. The initial condition is same as (A). (C) Stability of captured locomotion under perturbations. Over three equal time intervals random force vectors (N) whose strength were in ranges (1)[-0.1, 0.1], (2)[-0.5,0.5], (3)[-1,1] were exerted on each fin. The typical hydraulic force that a fin receives is around $\pm 0.3N$.

kinds of robots can be found in supplementary movie clips (http://email.kebi.com/∼necromax/explore.html). Although the movement patterns produced by our work can deviate from perfect patterns for highly adaptive locomotion, we believe it can make an important contribution as a basic exploratory element in more complex robotic system - such as providing supervisory pattern for the learning of locomotor CPGs.

References

Aida, T. and Davis, P. (1994). Oscillation mode selection using bifurcation of chaotic mode transitions in a nonlinear ring resonator. *IEEE Transactions on Quantum Electronics*, 30(12):2986–2997.

Asai, Y., Nomura, T., Sato, S., Tamaki, A., Matsuo, Y., Mizukura, I., and Abe, K. (2003). A coupled oscillator model of disordered interlimb coordination in patients with parkinson's disease. *Biological Cybernetics*, 88:152–162.

Barlas, Y. and Yasarcan, H. (2006). Goal setting, evaluation, learning and revision: A dynamic modeling approach. *Evaluation and Program Planning*, 29(1):79–87.

Buchli, J., Righetti, L., and Ijspeert, A. (2006). Engineering entrainment and adaptation in limit cycle systems. *Biological Cybernetics*, 95(6):645–664.

Davis, P. (1990). Application of optical chaos to temporal pattem search in a nonlinear optical resonator. *Japanese Journal of Applied Physics*, 29:L1238–L1240.

Ekeberg, O. (1993). A combined neuronal and mechanical model of fish swimming. *Biological Cybernetics*, 69:363–374.

Feudel, U. and Grebogi, C. (1997). Multistability and the control of complexity. *Chaos*, 7:597–603.

Iida, F. and Pfeifer, R. (2004). "cheap" rapid locomotion of a quadruped robot: Self-stabilization of bounding gait. In et al., F. G., editor, *Intelligent Autonomous Systems 8*, pages 642–649. IOS Press.

Kaneko, K. (1994). Relevance of dynamic clustering to biological networks. *Physica D*, 75(3):55–73.

Kuniyoshi, Y. and Sangawa, S. (2006). Early motor development from partially ordered neural-body dynamics: Experiments with a cortico-spinal-musculo-skeletal model. *Biological Cybernetics*, 95:589–605.

Kuniyoshi, Y. and Suzuki, S. (2004). Dynamic emergence and adaptation of behavior through embodiment as coupled chaotic field. In *Proceedings of IEEE International Conference on Intelligent Robots and Systems*, pages 2042–2049.

Morihiro, K., Isokawa, T., Matsui, N., and Nishimura, H. (2008). Effects of chaotic exploration on reinforcement learning in target capturing task. *International Journal of Knowledge-based and Intelligent Engineering Systems*, 12(5):369–377.

Nara, S. and Davis, P. (1992). Chaotic wandering and search in a cycle-memory neural network. *Progress of Theoretical Physics*, 88(5):845–855.

Ohgane, K., Ei, S., and Mahara, H. (2009). Neuron phase shift adaptive to time delay in locomotor control. *Applied Mathematical Modelling*, 33(2):797–811.

Ott, E., Sauer, T., and Yorke, J. (1994). *Coping with chaos: Analysis of chaotic data and the exploitation of chaotic systems*. John Wiley & Sons, Inc.

Pfeifer, R. and Iida, F. (2004). Embodied artificial intelligence: Trends and challenges. *Embodied Artificial Intelligence*, 3139:1–26.

Pitti, A., Lungarella, M., and Kuniyoshi, Y. (2009). Generating spatiotemporal joint torque patterns from dynamical synchronization of distributed pattern generators. *Frontiers in NeuroRobotics*, 3(2):1–14.

Raftery, A., Cusumano, J., and Sternad, D. (2008). Chaotic frequency scaling in a coupled oscillator model for free rhythmic actions. *Neural Computation*, 20(1):205–226.

Smith, R. (1998). Open dynamics engine (ode). http://ode.org/.